COMPARISON BETWEEN ECONOMIC AND ENVIRONMENTAL DRIVERS FOR DEMAND SIDE AGGREGATOR

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ABSTRACT

Demand-side flexibility is a promising source of the energy system that might enhance renewable energy penetration and help to democratize the electricity sector. However, it is not clear what is the best strategy to adopt for Demand Aggregators, especially when flexibility is provided by residential and tertiary buildings. This study compares two Demand Aggregators strategies in the framework of the SABINA (H2020) and the REFER research projects and analyses the effect of CO2 prices on the Demand Aggregator business model. Results show that Demand Response activities reduce both the costs and the building CO_2 emissions independently from the strategy adopted.

KEYWORDS

Demand-side Management; Demand aggregator architecture; Environmental aggregator

Glossary

Abbreviations

SO	System Operator
EMS	Energy Management System
DR	Demand Response
DA	Demand Aggregator
EV	Electric Vehicles
HVAC	Heating, Ventilation and Air Conditioning
ETS	Emission Trading System
PV	Photovoltaics panels
AEMS	Advanced Energy Management System
BA	Building Algorithm
MIDA	Market Integrated District Algorithm

Indices and sets

t € T	Time interval
i € I	Building

Variables

Ben	Economical benefits aggregator [€]
Pen	Economical penalization for not deliver the service [€]
Cost	Total costs for the flexibility activation [€]
u_{off}, d_{off}	Total upward and downward capacity offered by the aggregator at time t [kW]
$\emptyset$, β	Binary variables
d_{PV}	Downward regulation offered by the PV [kWh]
u_{batt}, d_{batt}	Total upward and downward deviation from battery baseline [kWh]
SOC	State of charge battery [kWh]
u_{hvac},d_{hvac}	Total upward and downward deviation from HVAC baseline [kWh]
$cost_{grid}$	Total costs from grid [€]
$cost_{CO2}$	Total costs for CO2 emissions [€]
$Flex^{+,-}$	Total upward or downward activated flexibility [kWh]
$Reb^{+,-}$	Upward or downward rebound effect due to flexibility activation [kWh]

Parameters

Δt	Time step considered
$p_{cap}{}^{+}$, $p_{cap}{}^{-}$	Capacity price at time t for upward and downward regulation [€/kW]
π^{+}, π^{-}	Percentage of upward and downward offered flexibility activate
P	Penalization to not respect the SO request
PV	Forecasted PV production [kWh]
η^{+}, η^{-}	Battery efficiency in charging/discharging
$SOC_{max,min}$	Maximum and minimum battery state of charge [kWh]
$\overline{P}_{\mathrm{ch}}$, $\overline{P}_{\mathrm{disch}}$	Maximum and minimum battery charging and discharging power [kW]
E_{ch}, E_{disch}	Baseline energy of charge/discharge to the battery [kWh]
R	Thermal equivalent resistance [kW/˚C]
C	Thermal equivalent capacitance [kWh/˚C]
COP	Coefficient Of Performance
$\overline{\Delta T}$,$\underline{\Delta T}$	Maximum and mínimum difference in the internal temperature from the set-point [˚C]
$\underline{P_{hvac}}$	Baseline power HVAC [kW]
$\overline{P_{hvac}}$	Maximum HVAC power [KW]
c_{grid}	Energy price from grid [€/kWh]
$price_{CO2}$	CO2 emissions price [€/kgCO2]
$CO2_{grid}$	CO2 emissions per kWh consumed from the grid [kgCO2/kWh]
$Base$	Baseline building consumption [kWh]

1. INTRODUCTION

The higher penetration of renewable energies in the electric system is creating new balancing challenges for System Operators (SO). Differently from conventional generators that can shape their production depending on the grid's necessity, sun, waves, and wind are stochastic energy sources that cannot be directly controlled. Indeed, the old paradigm in which the production follows the demand is not valid anymore and the ability to have flexibility from the demand side will be crucial for the stability of the electricity grid (Papaefthymiou et al., 2014) (Denholm and Hand, 2011). Moreover, the capacity to control the demand is also fundamental to reduce peak loads, when most pollutants power plants are active (Tahir et al., 2018). In this sense, demand side flexibility is a key element to reach environmental targets of countries and reducing greenhouse gas emissions (Shariatzadeh et al., 2015) at the same time that peak load reductions allow saving money while postpones the reinforcement of the electricity grid (Spiliotis et al., 2016).

Demand management technologies are already sufficiently mature to help the transition from passive consumers to active consumers, also called "prosumers". Demand flexibility begins with the acquisition of consumption measurements, which becomes fundamental (Brophy Haney et al., 2009), first, to be able to forecast the consumption for next day using the data harvested and second, to measure the contribution of each building to the grid in case of providing flexibility for balancing services. Thus, the spread of smart meters in Europe is valuable to measure the energy consumption of buildings in real-time. Then, new smart grid and building technologies, as Energy Management System (EMS), allow Demand Response (DR) by adapting the flexible loads. EMS are able to optimize the buildings' consumption and to react to external signals, i.e. economic or environmental among others. The main challenge is to transform these functionalities into products that consumers can trade in electricity markets (Iria et al., 2018) to reduce their electricity bill while helping the energy transition toward a 100% renewable energy system. However, although currently commercial buildings and residential consumers represent the major share of electricity consumption according to the International Energy Agency (Energy in Buildings and Communities Programme, 2016), their flexibility potential remains untapped. Hence, the first objective of this study is to analyse the flexibility potentials and possible approaches in residential and tertiary buildings.

In this context, the Demand Aggregator (DA) has emerged as the new market agent necessary to aggregate and manage demand-side flexibility (Bertoldi et al., 2016). The aggregation of the demand becomes necessary because the effect on the electricity grid of the consumption of an individual prosumer is negligible in comparison to the amount of energy necessary to balance the grid. Moreover, balancing markets have yet technical requirements designed for big centralized power plants, as for example the necessity to reach a minimum bid size. In addition, individual buildings do not have the capacity to optimize their participation in electricity markets because, for example, they are too small to manage the complexity (Bertoldi et al., 2016). It is the role of the DA to optimize the flexibility offers in the market during the day ahead and to optimize the real-time flexibility activation of its prosumers. To do so, it needs electricity market, consumption and flexibility forecasts for the next day and a communication protocol with its clients and other market actors.

There are mainly two strategies that a DA can follow: centralized or decentralized. The strategy adopted influences the degree of control and monitoring on the prosumers and it depends, among others, on the market framework, the type of prosumers involved, the information available from the prosumer and the objective of the DA. In a centralized strategy, the DA decides which prosumer to activate to reach its objectives. For instance, in (Iria et al., 2018) the DA adopts a centralize strategy by using the information from the EMS and the weather station to minimize costs of the DA in the energy market. The deep of knowledge in a centralized strategy is fundamental, as (Tang et al., 2018) demonstrates, where the DA needs to know even the charging events of the electric vehicles (EV), communicated by the EV owners. On the other hand, a decentralized strategy is presented in (Motalleb and Ghorbani, 2017) by applying a non-cooperative game theory model to allow prosumers to make flexibility offers to the DA, which has no information about the state of the prosumers. Cooperative solutions where prosumers collaborate between them to make the best offers to the DA, are also interesting alternatives for decentralized strategies (Malik and Ravishankar, 2018). In these later cases, the DA, has no role in the decision-making process.

Currently, DA have large energy consumers such as big industries in their portfolio, while in Europe just a few of them deal with buildings (Shoreh et al., 2016). However, literature is focusing as well on residential and tertiary buildings. For instance, in (Siano and Sarno, 2016) the DA adapts the consumption of the Heating, Ventilation and Air Conditioning (HVAC) and shiftable loads of residential prosumers according to the price of energy. Or in (Lipari et al., 2018) the DA aggregates small consumers at the low voltage level with the objective to solve congestions of the distribution grid.

With the aim to better explore the possibilities of different strategies adopted by residential or tertiary DA, the second objective of the study is to analyse the differences among two aggregators' objectives, architectures, and strategies in the

framework of two research projects: the H2020 project SABINA (“SABINA,” 2018) and the REFER project (“REFER,” 2018).
In order to limit the global warming to 1.5 degrees above preindustrial levels, as set in the Paris agreement, carbon pricing mechanisms are often considered a key part of the policy mix (Mundaca et al., 2019). In 2016, about 15% of global GHG emissions were priced directly via a tax or emissions trading system (ETS) (World Bank, Ecofys, 2017). However, there is not yet an accepted scheme to evaluate the CO2 savings of DR measures and different strategies are proposed in literature (La Réseau de Transport d’eléctricité, 2017). The main difficult is to assess the real value of DR in terms of emission savings, as there are real time implications, depending on the hourly generation mix, but also long-time implications for allowing increased share of renewable energies and dismiss most pollutant power plants (COWI et al., 2016). In this study, the real time impact of DR is taken into account to evaluate the CO2 savings of the DA. With the aim to better understand the implications that the participation of DA in ETS would have on the DA business model, the aggregator’s strategies will be analysed under three different scenarios of CO2 emission allowance.
The remaining part of the paper is organized as follows: Section 2 describes the buildings analysed and the architectures and strategies of the two DA presented. Section 3 describes the mathematical model used to define the bidding strategy of the two DA. Section 4 shows and discusses the results obtained. Concluding remarks and suggestions for further research are given in the final section.

2. MATERIALS AND METHODS

For one side, this section describes the characteristics of the flexibility sources available in the analysed buildings. On the other side, the section presents the DA objective, architectures, strategies and pricing in the two projects indicated above.

Description of flexibility sources in buildings

With the objective to easily understand and identify the main characteristics and activation processes of the two DA compared in this study, the flexibility potential focus on a small library and a household during one day, although both DA have several buildings in their portfolio. The day analysed is the 5th of March 2019.

In the REFER project, the DA takes advantage from the flexibility of the 61 public libraries of the Metropolitan Area of Barcelona, however, as mentioned above, data are gathered only from the Montgat library. The library is equipped with Photovoltaics panels (PV), a second life EV battery, and a HVAC system. The PV on the rooftop provides up to 19 kW peak power. The second life battery, with a capacity of 18.4 kWh and the power limited to 10 KW by the converter, stores the surplus of energy from the PV panels, as in (Canals Casals et al., 2019a). The HVAC installed assures the thermal comfort in the library and has a power peak of 39 kW, being it able to produce 126 kW of heat and 116 kW of cold. The commercial EMS installed charges the battery during the night, when the energy is cheaper, to use that energy during the day, when it is more expensive. Finally, the EMS controls the HVAC assuring that the internal temperature of the building is equal to the temperature of set point.

On the other hand, the SABINA project is based on residential buildings. SABINA focuses the attention on a simulated 4-floor building with one dwelling per floor of about 105m^2 located in the city of Tarragona. Similarly to the library in Montgat, this building has PV panels installed on the rooftop that provide up to 2.7 kW peak power. To store the surplus coming from this generation, the building is equipped with a community battery of 10 kWh capacity and 4 kW power peak. Additionally, the building can use two EV with 24 kWh battery capacity to smartly control the charges when plugged. Finally, each dwelling counts on an independent 15 kW thermal power heating system. An advanced energy management system (AEMS) procures to minimize the injection of energy to the electricity grid by taking advantage of the batteries, the EVs and regulating the temperature set point of the spaces in the house. The main difference between an EMS and an AEMS is that the second one has higher computational power, being able to forecast the energy consumption, and to calculate the flexibility capacity and the rebound effect caused by flexibility requests using models of the building and equipment within together weather and historical consumption data. Figure 1 shows the two buildings analysed.


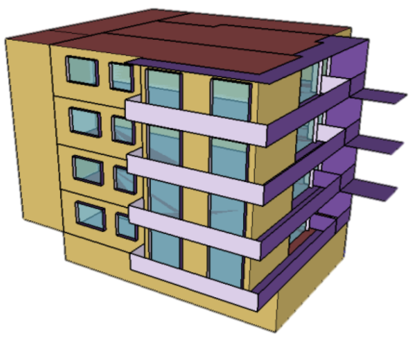

Figure 1: Mongat’s library from REFER (left) and Simulated building for the SABINA project (right)

In both cases, it is assumed that stationary batteries can be used to balance the grid without exceeding the maximum power allowed and the physical limits of the battery capacity. The HVAC is able to provide flexibility by changing the set point temperature during a certain period within the temperature ranges agreed with the building owner. In the library of the REFER, the maximum temperature variation from the set point temperature is set at 2 ºC when it is open and 5 ºC one hour before it opens and one hour after it closes, as it is not necessary to assure the thermal occupant's comfort in this case. In SABINA, users accept a temperature variation of 3 degrees. Regarding the generation of energy, PV panels can provide flexibility if necessary by cutting the production in REFER, while in SABINA there is no possibility to stop the PV generation, being unable to use them as a flexibility source. Finally, in the SABINA project, EVs act as an additional flexibility source as the AEMS can change the building consumption through the forecast of the EV energy charge needs and of the period when the vehicle is expected to be plugged in (as described in (Canals Casals et al., 2019b) and also because it can shift the EV charge from one period to the other and modulate the power injected to the EV through smart charging. Note that the AEMS ensures that the EV is charged enough so the owner should be capable of driving the car for the whole trip but it has no restriction such as having to have a full charged battery at a certain hour. Table 1 resumes the controllable devices considered in each project.

Another difference to keep into account when comparing residential and tertiary buildings is the occupancy behaviour. Tertiary buildings have fixed daily and weekly schedules repeated every week, which make it easier to forecast energy consumption. On the contrary, residential buildings have less predictable consumption patterns (O'Neill and Niu, 2017). In addition, during the day, libraries are usually open at full operation and household are more likely to be empty.

	REFER	**SABINA**
Heat	✓	✓
Cold	✓	
Stationary battery	✓	✓
EV		✓
PV	✓	✓*
AEMS		✓

Table 1 Appliances considered in each project

**Although SABINA has PV panels installed, no production control is available.*

DA objectives, systems architecture, and information chain

This sub-section presents the basic architectures and strategies of both DA.

The first and maybe most important difference between the two strategies analysed in this study is the objective of each DA. In the previous section it has been already mentioned that, in SABINA, the system counts on an AEMS with high computational characteristics. This fact is relevant as, in this project, there are two algorithms running simultaneously at different levels: The AEMS has a Building Algorithm (BA) that controls the consumption of the building to maximize self-consumption while the DA runs an algorithm on top named Market Integrated District Algorithm (MIDA) that interacts with the BA whenever it is necessary.

SABINA's MIDA main goal is to minimize the greenhouse gas emissions of its clients analysing data from the electricity mix of the grid as a driver in the decision-making. Additionally, the algorithm developed assures no additional costs for the consumers.

On the contrary, in the REFER project the main objective of the DA is to obtain economic benefits for the aggregator and its clients. Therefore, balancing market prices are taken as the main driver in the DA decision-making.

Although in a different way, both approaches consider economic revenues for the activation of flexibility. Thus, in both cases they need to somehow "predict" the costs (with regards to the use of energy) and payments (with regards to the participation on electricity markets) of electricity to perform the optimization. Once done, the DA uses the final real costs and payments to evaluate the goodness of the activations.

As building's flexibility hardly offers succulent economic incentives to boost the entrance of DR (Zheng et al., 2014), this study includes the carbon trade as an additional possible income to consider for the bidding strategy. Figure 2 shows the evolution of the price of carbon trade markets within EU for the last 3 years. Notice how the trend since 2017 is to continuously increase, showing how the price is now around 25 €/tCO_2 eq. while in 2017 it was less than 5 €/tCO_2 eq. meaning that within this period prices have raised about 500%. Following this trend, it could be expected that, in 2030, prices should be close to the 95€/tCO_2 eq. considered in literature (La Réseau de Transport d'eléctricité, 2017).

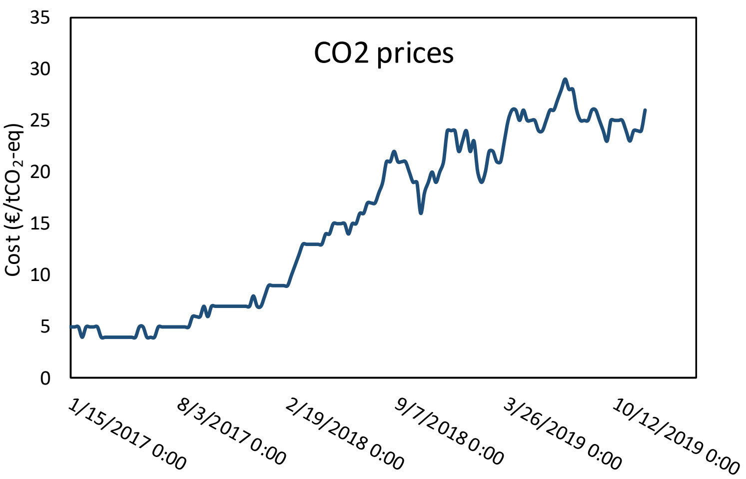

Figure 2: Evolution of the carbon trade market since 2017 (https://sandbag.org.uk/carbon-price-viewer/)

For the study, three scenarios with and without the consideration of this carbon-trade possible revenue are presented, showing its impact in the decision of choosing one activation or another. The first one considers no CO2 emission allowance for DR, that is the actual situation; the second one considers a price for CO2 emission allowance equal at the CO2 emission allowance at the end of 2019, that is 25 €/tCO_2 eq.; the third one considers an expected price for CO2 emission allowance for 2030, that is 95 €/tCO_2 eq.

In both cases it is assumed that a percentage of the total amount of energy offered will be activated since this is what commonly occurs in these kinds of markets. In REFER, this percentage is higher than 30 % of the flexibility offered while in SABINA the energy activated is a random value taken from a normal distribution centred at 30% and with a 5% standard deviation. To calculate total benefits, both systems consider the utilization and capacity prices in the secondary electricity market in Spain ("esios red eléctica de España," 2018). In the same way, to calculate emissions from the grid during a certain hour, the energy mix of that hour in Spain is considered. Table 1 shows the information used by the algorithms of the two projects presented in the bidding strategy optimization and in the evaluation of the results. Note that, the red mark indicates that this information is the signal used as driver to achieve the main goal of the DA.

		Optimization		Evaluation	
		SABINA	**REFER**	**SABINA**	**REFER**
Market	Grid tariff [€/kWh]	✓	✓	✓	✓
	Capacity price secondary market [€/MW/h]	✓	✓	✓	✓
	Utilization price secondary market [€/kWh]	✓	✓	✓	✓
	CO_2 emissions [gCO_2/MWh]	✓		✓	✓
Building	Baseline consumption from the AEMS [kWh]	✓			
	Flexibility availability from the AEMS [kWh]	✓			
	Rebound effect flexibility from the AEMS [kWh]	✓			
	Consumption from the smart meter [kWh]		✓		
	PV forecasts from the weather station [kWh]		✓		
	Building characteristics		✓		

Table 2 Information used in each project in the optimization and in the evaluation phase

DA strategy and architecture strongly depends on the information available from the prosumers and on the objective function of the DA. In the REFER project, the DA does not receive any specific or predefined information from buildings; in fact, it is the same DA that forecasts the baseline and the flexibility of its prosumers thanks to the information available from the smart meters and weather data and determines when to activate them. This means that all the intelligence of the system is located in the DA. That is, the DA forecasts the consumption of buildings during the day before and optimizes the bids in electricity markets. In this case, the prosumers do not have any role in the decision-making process and they won't need to install any AEMS to be part of the DA portfolio. When the grid requests some energy, the DA sends activation messages (consisting on set points for the appliances) to the buildings' EMS depending on its own forecasts. If the aggregator request does not violate any comfort limit in the building, the EMS follows the indication of the DA. In this case, the DA is also in charge to control if the EMS is effectively following its request and if not, other prosumers in its portfolio are activated.

On the contrary, in the SABINA project, it is the AEMS of each building that forecasts the baseline consumption and the flexibility. Then, once per day, the AEMS sends this information (named Flexibility Map) to the DA. With this information from all the buildings in the neighbourhood, the DA optimizes the flexibility offers to the market for the next day. Additionally, the DA has access to the real-time measurements of the smart meters and to the information communicated by the AEMS, every 15 minutes, of an updated consumption baseline considering the latest events. When the DA sends an activation message to the AEMS 30 minutes before the activation occurs, which consist on an amount of energy to increase/decrease, the AEMS responds with what the building will be capable to perform. This response might be different to what was computed in the Flexibility Map from the day ahead due to the changes in the building consumption along the day. With these responses, the MIDA re-allocates all the energy among its portfolio according to the reliability index and sends the confirmation or not to activate the flexibility with the amount of energy indicated in the response of the building. A detailed analysis of the modules forming MIDA and their relations and actions can be read at (Casals et al., 2019). In SABINA, the DA is closer to an intermediary between buildings and markets who chooses which building will finally participate in the activation. Prosumers do not lose the control on their appliances but they would need an AEMS that complies with the DA messaging and computing requirements to be able to be part of its portfolio.

Figure 3 represents the information flow between aggregator and buildings of the two DA described. Note the main differences represented, which are: the driver of the DA (environmental vs economic) and the computation efforts (brains). In REFER the DA performs most of the calculations while the EMS is the executor (work tools). In SABINA the computation effort is combined, where the DA optimizes and evaluates flexibility activations while the AEMS computes the flexibility capacity and energy delivering during activations. For this reason, the weather information (1) goes to different "intelligent" systems, which are the ones in charge to calculate the flexibility available for the next day (2). See how, in SABINA, the flexibility capacity is sent from the AEMS to the DA (3), not being so in REFER, as the DA is the one computing it. In both cases the DA optimizes the flexibility bid for the next day (4). When a flexibility activation is requested by the markets (5), in REFER the DA communicates a set point for the appliances to the EMS (6-7), which just execute the order (8). On the contrary, in the SABINA, the DA just communicates the consumption limits to the AEMS (6), which is in charge to control all the appliances computing the set points to be used by itself (7).

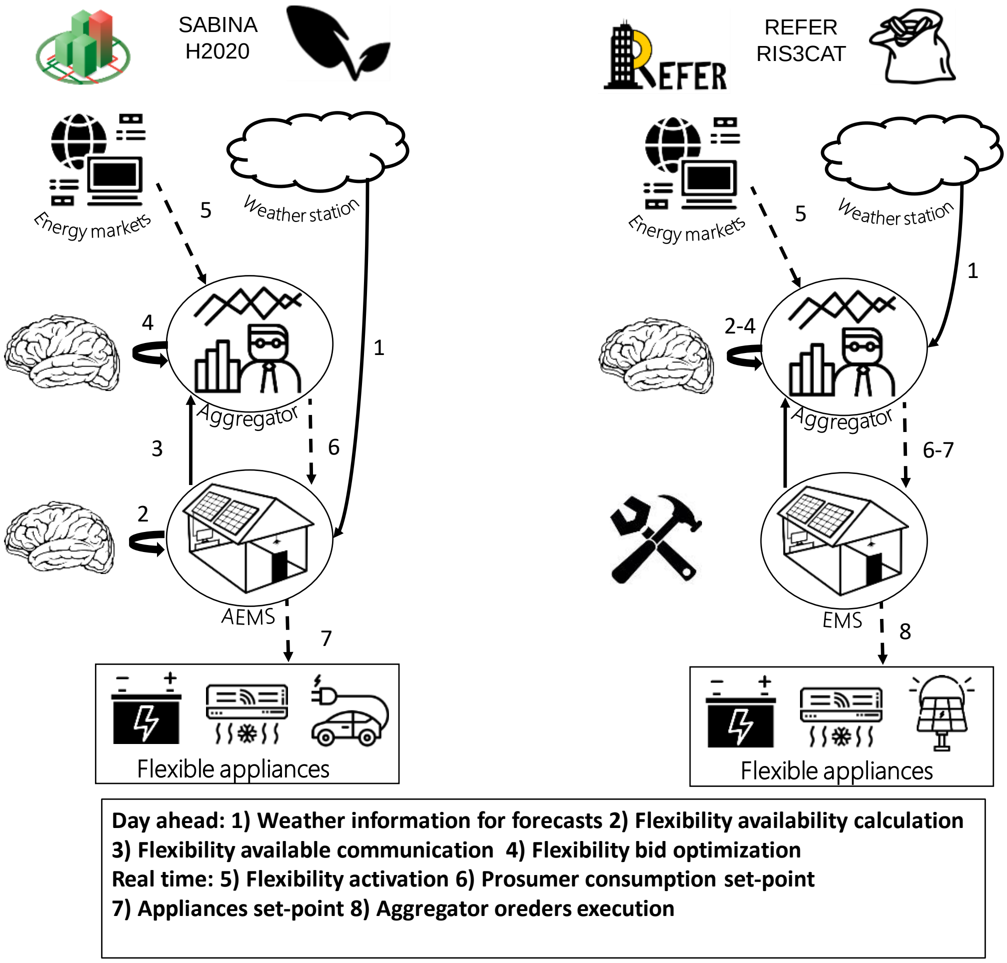

Figure 3 Comparison of the system architecture in the two analysed projects

Another important difference between the two projects is that in SABINA, the DA can activate the flexibility of the prosumers once per day while in REFER the DA can activate the libraries as many times as it is necessary with the only restriction to respect the comfort limits at all times.

3. CALCULATIONS

In both case studies, the optimization problem defines the bidding strategy of the aggregator for the day ahead reserve market. Throughout the paper it is assumed that the aggregator is a price taker, because the reserve provided does not change the resulting market price. In REFER, the DA knows the quantity and the direction of the reserve activated for next day not being so in the case of SABINA.

As highlighted in Section 3, the REFER aggregator offers flexibility at all hours, as there are not constrains on the maximum number of activations from the prosumers. The used formulation is linear and the objective function to minimize is Eq. (1), which has three terms: the benefits (*ben)*, the eventual penalizations (*pen*) to not fit the SO request and the consumer's additional costs due to the flexibility activation (*cost).*

$$\text{Min } (\sum_{i=1}^{I} \sum_{t=1}^{T} - ben(t) + pen\ (t) + cost(t)) \qquad \forall \text{ t} \in \text{T} \qquad (1)$$

The benefits are calculated using Eq. (2). Where u_{off} and d_{off} represent the upward and downward flexibility offered, $\pi^{+,-}$ represent the percentage of the offered flexibility finally activated, ${\text{p}_{\text{cap}}}^{+,-}$ is the capacity price [€/kW] of the upward and downward reserve and ${\text{p}_{\text{en}}}^{+,-}$ is the utilization payment [€/kWh]. Note that the auxiliary variable $\emptyset(t)$ takes value equal to 1 when the aggregator follows the orders of the SO.

$$ben(t) = \emptyset(t) * \Delta\text{t} * (u_{off}(t) * \left({\text{p}_{\text{cap}}}^{+}(\text{t}) + \pi^{+}(\text{t}) * {\text{p}_{\text{en}}}^{+}(t)\right) + d_{off}(t) * \left({\text{p}_{\text{cap}}}^{-}(\text{t}) + \pi^{-}(\text{t}) * {\text{p}_{\text{en}}}^{-}(t)\right)) \ \forall \text{ t} \in \text{T} \quad (2)$$

Eq. (3) models the penalizations, which appear in case the DA is not able to provide the flexibility requested by the SO. The value of P is fixed at 0.3, which means that, if the aggregator does not fulfil the SO request, apart from not being paid during that hour, it suffers an additional penalization equal to the 30 % of the expected earnings.

$$pen\ (t) = P * \left(1 - \emptyset(t)\right) * \ (u_{off}(t) * {\text{p}_{\text{cap}}}^{+}(\text{t}) + d_{off}(t) * {\text{p}_{\text{cap}}}^{-}(\text{t})) \qquad \forall \text{ t} \in \text{T} \qquad (3)$$

Finally, the flexibility's activation costs is the sum of the cost of the use of energy from the grid ($cost_{grid}(t)$) and of the emissions' trade due to the generation of electricity in the electricity mix. This cost can either have positive and negative values and two equations (Eq. (4) and (5)) are used to calculate it:

- Grid costs $cost_{grid}(t)$: The costs/benefits for changing the quantity and the time in which energy is consumed, represented in Eq. (19). $c_{grid}(t)$ is the grid tariff [€/kWh] at time *t*.
$$cost_{grid}(t) = (-u_{batt}(t) + d_{batt}(t) - u_{hvac}(t) + d_{hvac}(t) + d_{PV}(t)) * \ c_{grid}(t) \qquad \forall \text{ t} \in \text{T} \qquad (4)$$
- CO_2 costs $cost_{CO2}(t)$: The cost/benefits due to the carbon tax, represented in Eq.(20). $price_{CO2}$ [€/kgCO_2] is the actual CO_2 price, while $CO2_{grid}(t)$ [kgCO2/kWh] indicates the CO_2 emissions for each kWh consumed from the grid.

$$cost_{CO2}(t) = (-u_{batt}(t) + d_{batt}(t) - u_{hvac}(t) + d_{hvac}(t) + d_{PV}(t)) * \ (price_{CO2} * \ CO2_{grid}(t)) \quad \forall \text{ t} \in \text{T} \quad (5)$$

Note that, effectively, several elements within the library are used to compute these costs. Thus, the complete formulation to calculate the total costs include the modelling of each one of the technologies controlled by the DA.

In the case of the PV, which are able to reduce their production, the only constraint is Eq. (6), which assures that the flexibility activated at time *t* by the PV d_{PV} is lower than the forecasted PV production PV(t).

$$d_{PV}(t) \leq PV(t) \ \ \forall \text{ t} \in \text{T} \qquad (6)$$

The optimization of battery charging and discharging strategy requires 5 constrains. The assumption is that the DA knows what is the charging/discharging strategy of the battery without any flexibility activation, as in (Canals Casals et al., 2019a), given by $E_{ch,disch}$. Eq. (7) sets the SOC of the battery, which is equal to the SOC at the previous time step plus the baseline energy of charge/discharge, plus the upward/downward flexibility offered by the battery, $u_{batt}(t)$ and $d_{batt}(t)$ respectively. The parameters η^{+} and η^{-} are the efficiency of the charging/discharging process. Eq. (8) assures the SOC within its limits OC_{min} SOC_{max}. Eq. (9) guarantees that the charging and discharging energy does not exceed the maximum charging and discharging power $\overline{P}_{\text{disch}}\Delta\text{t}$ and $\overline{P}_{\text{ch}}\Delta\text{t}$ respectively. Eq.(10) and (11) assure at the same time that the activated flexibility is lower than the maximum power allowed and that the flexibility is activated just in one direction during one time step, thanks to the binary variable β.

$$SOC(t) = SOC(t-1) + (E_{ch}(t) + \ d_{batt}(t)) * \ \eta^{+} - \ (E_{disch}(t) + \ u_{batt}(t)) / \ \eta^{-} \qquad \forall \text{ t} \in \text{T} \qquad (7)$$

$$SOC_{min} <= SOC(t) <= SOC_{max} \qquad \forall \text{ t} \in \text{T} \qquad (8)$$

$$-\overline{P}_{\text{disch}} \leq (E_{bat_{ch}}(\text{t}) + \text{d\_batt(t)} - E_{bat_{disch}}(\text{t}) - u_{batt}(t))/\Delta\text{t} \leq -\overline{P}_{\text{ch}} \qquad \forall \text{ t} \in \text{T} \tag{9}$$

$$u_{batt}(t) \leq \beta(t) *(\overline{P}_{\text{disch}} + \overline{P}_{\text{ch}})* \Delta\text{t} \qquad \forall \text{ t} \in \text{T} \tag{10}$$

$$d_{batt}(t) \leq (1 - \beta(t)) *(\overline{P}_{\text{disch}} + \overline{P}_{\text{ch}})* \Delta\text{t} \qquad \forall \text{ t} \in \text{T} \tag{11}$$

The HVAC model adopted is a resistor-capacitor (RC) equivalent model which describes its operations is represented in Figure 4.

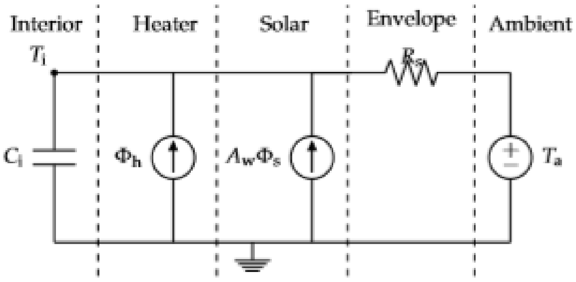

Figure 4 RC equivalent model used in the REFER builduing's model (Bacher and Madsen, 2011)

The equations that describe this model are Eq.(12) and (13), where *Ta* represents the ambient temperature, *Ti* is the internal builduing temperature, *Aw* is the transparent surface of the builduing, Φ_s is the solar irradiation and Φ_h represents the termal load provided by the HVAC system. *K* indicates the number of available measures and the error ε_k is assumed to follow a normal distribution $N(0, \sigma_\varepsilon^2)$.

$$dT_i = \left(\frac{1}{RC} * (Ta - Ti) + \frac{1}{C} A_w \Phi_s + \frac{1}{C} \Phi_h\right) dt + \sigma_i d\omega_i \tag{12}$$

$$Y_k = T_i + \varepsilon_k \tag{13}$$

The values of the thermal resistance *R* [kW/°C], the thermal capacity *C* [kWh/°C], the building's transparent surface *Aw* [m^2] and σ_ε are optimized using the R library "ctsrm" (DTU, 2018) . From Eq.(12) and (13) it is possible to assume that to keep the building at the set-point temperature it is necessary to keep the dT_i equal to 0 (Eq. (14)).

$$\frac{1}{RC} * (Ta - Ti) + \frac{1}{C} A_w \Phi_s = \frac{1}{C} \Phi_h \tag{14}$$

Here Φ_h is the baseline HVAC power, but the objective is to calculate the available $\Delta\Phi_h$, which represents the difference between the baseline power and the real power used by the HVAC. For the first hour, the relation between $\Delta\Phi_h$ and the difference in the internal temperature ΔT is represented in Eq. (15), as all the other parameters are maintained constant.

$$\Delta\text{T(t)} = \frac{1}{C} * \Delta\Phi_h(t) \qquad \forall \text{ t} \in \text{T} \tag{15}$$

Finally, during all the other time steps the temperature building behavior is represented in Eq. (16).

$$\Delta\text{T(t)} = \frac{1}{C} * \Delta\Phi_h(t) + \frac{1}{RC} * \Delta T(t-1) \qquad \forall \text{ t} \in \text{T} \tag{16}$$

In order to test the optimized parameters R and C it was simulated a flexibility activation from 15:00 to 15:45 during the 15/07/2019 in Montgat's library. During this time, the set point temperature (orange line) was changed from 24 to 25 ºC. The dark blue line in Figure 5 represents the baseline HVAC power (here the previous day was taken as a reference), while the light blue line represents the real power consumed during the day considered. The grey line represents the real internal temperature of the building. The estimated internal temperature (green line) is the sum between the ΔT(t) calculated (Eq. 14) and the internal temperature during the previous day. Figure 5 shows that the HVAC power diminishes during the activation, while there is a rebound effect during the next half hour. Regarding the temperatures, the estimated temperature follows the same pattern as the real temperature. The maximum error is of 0.74 ºC, which is acceptable, as it is lower than the sensibility of the measurement instrument.

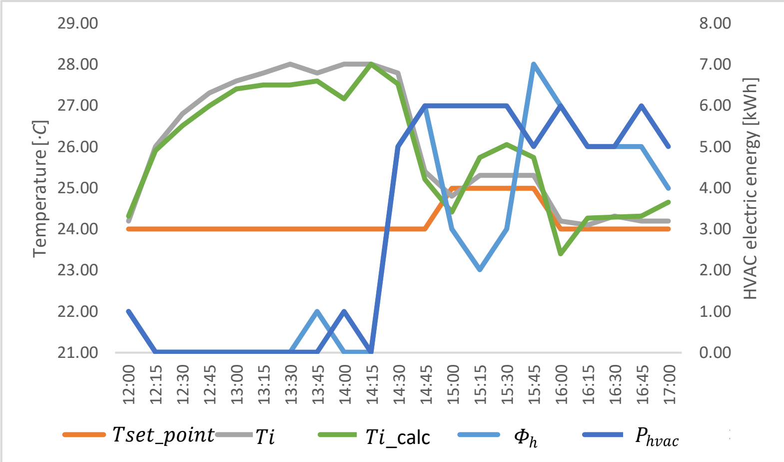

Figure 5 HVAC real and base power, set point temperatures, real and calcultated interior temperature of the test-day in Montgat library

By formalizing the previous equations, the HVAC model requires 4 constrains. Eq.(17-18) model the internal temperature of the building during the first time step and during the rest of the day respectively in case of upward or downward HVAC activation u_{hvac} and d_{hvac}. Note that to pass from the electric to the thermal power the HVAC Coefficient of Performance (COP) is used. Eq.(19) assures that the ΔT remains ever in the comfort limits $\underline{\Delta T}$ and $\overline{\Delta T}$, while Eq.(20) guarantees that the electric power of the HVAC does not exceed its power limits, taking into account the baseline power of the HVAC at time *t* P_{hvac}.

$$\Delta T(t) = \frac{1}{C} * (-u_{hvac}(t) + d_{hvac}(t)) * COP \quad \forall\, t \in T \tag{17}$$

$$\Delta T(t) = \frac{1}{C} * (-u_{hvac}(t) + d_{hvac}(t)) * COP + \frac{1}{RC} * \Delta T(t-1) \quad \forall\, t \in T \tag{18}$$

$$\underline{\Delta T} \leq \Delta T(t) <= \overline{\Delta T} \qquad \forall\, t \in T \tag{19}$$

$$0 \leq \left(-u_{hvac}(t) + d_{hvac}(t)\right)/\Delta t + P_{hvac}(t) <= \overline{P_{hvac}} \qquad \forall\, t \in T \tag{20}$$

On the other hand, SABINA's DA decides when to activate the flexibility by minimizing the emissions according to Eq. (21), which is divided in two blocks that are yet divided in two additional sub-blocks. The high level blocks refer to the direction of flexibility (- downwards and + upwards) and the lower level blocks refer first to the emissions' increase or decrease during the flexibility activation and second, during the corresponding rebound effect.

$$f(MIDA) = Min \sum_{t=0}^{24} \sum_{i}^{n} (((\beta_i^-(t) * Flex_i^-(t) * CO2_{grid}(t)) - \sum_{1}^{r}\left(Base_i(t+r) - Reb_i^-(t+r)\right) * CO2_{grid}(t+r)) - \left(\left(\beta_i^+(t) * Flex_i^+(t) * CO2_{grid}(t)\right) - \sum(Reb_i^+(t+r) - Base_i(t+r)) * CO2_{grid}(t+r)\right) \qquad \forall\, t \in T,\ \forall\, i \in I \tag{21}$$

When the variable $\beta_i^-(t)$ is set to 1 it means that the flexibility is required, while a value of 0 means that no flexibility will be activated. The *i* is the indicator of a building in the DA portfolio. Then, $Flex_i(t)$ is the flexibility capacity reported by building *i* at a certain hour *t*. Note that, for each capacity per hour and building, the equation computes the emissions of the rebound effect as the subtract between the baseline expected consumption $Base_i(t+r)$ and the change in the consumption $Reb_i^+(t+r)$ for the whole duration of the rebound effect *r*.

As already mentioned, the cost function is set as a constraint to the model and not as something to optimize. The only condition is that there should be no additional cost for the owner of the building whenever flexibility is activated. As the DA does not have any input on which elements in the buildings are used to deliver a certain amount of flexibility, it is obliged to use electricity costs and payments only, as shown in equations (22-26). Note that equations (22-23) are similar to the one used in the REFER project to determine the optimal use but in SABINA they act only as a restriction.

$$ben_i^+(t) - cost_i^+(t) \geq 0 \qquad \forall\, t \in T, \forall\, i \in I \tag{22}$$

$$ben_i^-(t) - cost_i^-(t) \geq 0 \qquad \forall\, t \in T, \forall\, i \in I \tag{23}$$

Where the profit obtained through the participation in the market are identified as *ben(t)* and defined through Eq.(24) and the costs of flexibility *cost(t)* are defined in eq.(25-26). It is important to notice that there is a condition for upwards and another for downwards. This is because benefits for capacity compute in both directions even when there will be only one direction of activation at a time. See how Eq.(24) considers the payments for capacity in both directions as $\mathrm{p_{cap}}^{+-}(\mathrm{t})$ and the payments for energy used is considered only in one direction $\mathrm{p}_{en}(t)$ and considering only a part of the total energy offered by using π (ratio between the offer and what could really be used). Note also that the third term multiplied by the CO_2 emissions is only relevant when taking into consideration the carbon trade prices.

$$ben^{+}(t) = \mathrm{p_{cap}}^{+}(\mathrm{t}) * Flex_i^{+}(\mathrm{t}) * \beta_i^{+}(\mathrm{t}) + \mathrm{p_{cap}}^{-}(\mathrm{t}) * Flex_i^{-}(\mathrm{t}) * \beta_i^{-}(\mathrm{t}) + \mathrm{p}_{en}(t) * \pi\,(t) * Flex_i(\mathrm{t}) * \beta_i(\mathrm{t}) + price_{CO2} * CO2_{grid}(t) * \pi\,(t) * Flex_i(\mathrm{t}) * \beta_i\,(\mathrm{t}) \qquad \forall\, \mathrm{t} \in \mathrm{T}, \forall\, \mathrm{i} \in \mathrm{I} \qquad (24)$$

On the other side, the term related to the costs of energy refers to the implications of the rebound effect and it is explained by Eq. (25-26). Additionally, the emissions' trade of the rebound effect is also taken into consideration.

$$Cost^{+}(\mathrm{t}) = -\,Savings\ of\ decreasing\ consumption\ at\ t\ in\ a\ building + rebound\ effect\ costs\ = (-c_{grid}(t) * \ Flex^{+}(t)\ + \textstyle\sum_1^r\ (c_{grid}((t+r) + price_{CO2} * CO2_{grid}(t)) * (Reb_i^{+}(t) - Base_i(t)) + \ ) * \pi\,(t) * \beta_i^{+}(t) \qquad \forall\, \mathrm{t} \in \mathrm{T}, \forall\, \mathrm{i} \in \mathrm{I} \qquad (25)$$

$$Cost^{-}(\mathrm{t}) = Cost\ of\ increasing\ consumption\ at\ t\ in\ a\ building - rebound\ effect\ savings\ = (c_{grid}(t) * \ Flex^{-}(t) - \textstyle\sum_1^r\ (c_{grid}(t)\ * CO2_{grid}(t)) * (Base_i(t) - Reb_i^{-}(t+r))) * \ \pi\,(t) * \beta_i^{-}(t) \qquad \forall\, \mathrm{t} \in \mathrm{T}, \forall\, \mathrm{i} \in \mathrm{I} \qquad (26)$$

Note that, as the description of upwards and downwards capacity is written from a grid generation control perspective, Upwards flexibility means a reduction of the consumption of a building (thus, savings) while downwards flexibility means an increase of consumption and, consequently, costs.

In summary, it is expected that the emissions' trade prices will have no effect in the optimization results of SABINA, who's main goal is environmental and the decision is not directly affected by costs, but could have an impact on REFER, as a change in the economic rules does directly implies a change in the optimization results.

4. RESULTS AND DISCUSSION

The consumption pattern is obviously reflected in the estimation of the flexibility curve. Figure 6 shows the baseline consumption from the grid and the estimation of the flexibility available of the two buildings analysed during the 5th of March 2019. Notice that the shape of the flexibility and consumption curves vary between residential and tertiary buildings. Occupation issues cause that, while households are stochastically occupied during the whole day, having a higher energy use at morning and night, most of the tertiary buildings have opening times and are generally closed at night and on weekends. For this reason, tertiary buildings' flexibility potential to reduce consumption during the night is negligible, while they have the potential to increase their consumption during those hours. Indeed, residential buildings' flexibility potential is more constant than that of a tertiary building. Additionally, as the building in SABINA has an EMS that tries to minimize the consumption, the availability of flexibility upwards (to reduce the consumption of the building) is scarce.

However, in both cases the flexibility potential depends on weather conditions and in particular on the HVAC consumption: if the HVAC is off, the flexibility potential to decrease the consumption is null without storage systems installed, this means that the flexibility has high seasonality dependence and even more in the case of SABINA, where only heat pumps are available.

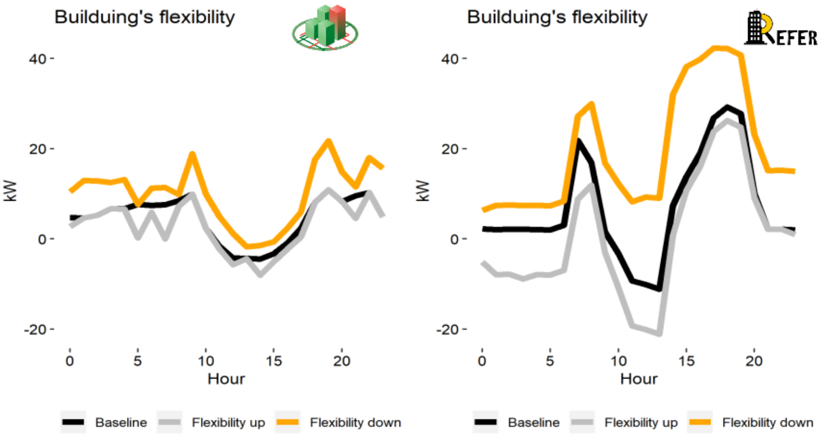

Figure 6 Flexibility comparison among buildings

In the case of the REFER, the DA is implicitly able to optimize the building consumption, in addition to optimize its bidding strategy and to manage the flexibility activations. In fact, during the 5th of March, the DA saved 39 kWh of consumption from the grid over 250 kWh of original demand. In majority, **this reduction is due to a reduction of the building temperature when upward reserve is activated**. Thanks to this reduction, the building emits 4.79 kg CO_2 less than if the DA would not have operated in the building, equivalent to a 20% of its total emissions.

From an economic perspective, the DA optimization brings a reduction in the electricity costs of about 18 €, being the participation in balancing markets responsible of most of them with 14.12 €, of which 5.75 € come from capacity and 8.37 € from utilization payments. Only 4.02 € are caused by the implicit reduction costs from the grid. Supposing that 80 % of the aggregator's gain would go to the users, during this day the library would be able to save the 26 % of its energy costs. The total energy shifted up or down by the library to balance the grid is 198.75 kWh during the day considered. The building saves 0.024 Kg of CO_2 equivalent emissions per kWh shifted, while it gains 0.09 € per kWh shifted.

Independently from the CO_2 price considered, the DA uses exactly the same bidding strategy, as the price signal is still too low to influence its decisions. In fact, there is a very low income difference among scenarios, being the incomes in the scenario without CO_2 price equal to 18.34 € and considering a CO_2 price of 95€/tCO_2 eq. it slightly increases up to 18.82 €. This increase represents an income increase of 2.6 %. However, it is important to highlight that in the market considered, offers are done by quarters of hour, while the energy mix published by RTE is the hourly energy mix. For this reason, the DA is not incentivized to move its offers from a quarter of hour to the other, as there will be probably the same energy mix.

In the case of SABINA, the system knows the expected consumption before the activation (as it receives the projected baseline for the next hours), so it is possible to analyse in detail the effects of the activation. Note that, for the 5th of March, the accumulated emissions and energy cost of the building were about 13.59 kg of CO_2 equivalent emissions and 11.29 €. Moreover, the activation of flexibility was upwards (that is, a reduction in the consumption of the building) of about 8 kWh at 7h in the morning. See the relevant decrease in energy consumption at that hour in Figure 7. This sole activation supposed (against the expected baseline of 1h prior to the activation for the rest of the day) savings of around 2.66 kg of CO_2 equivalent emissions and 2.68€ (of which 0.35€ come from capacity (0.04€), use of energy (0.31€) payments from balancing markets). This means that most of the incomes are caused by a change in the rebound effect against the predicted baseline.

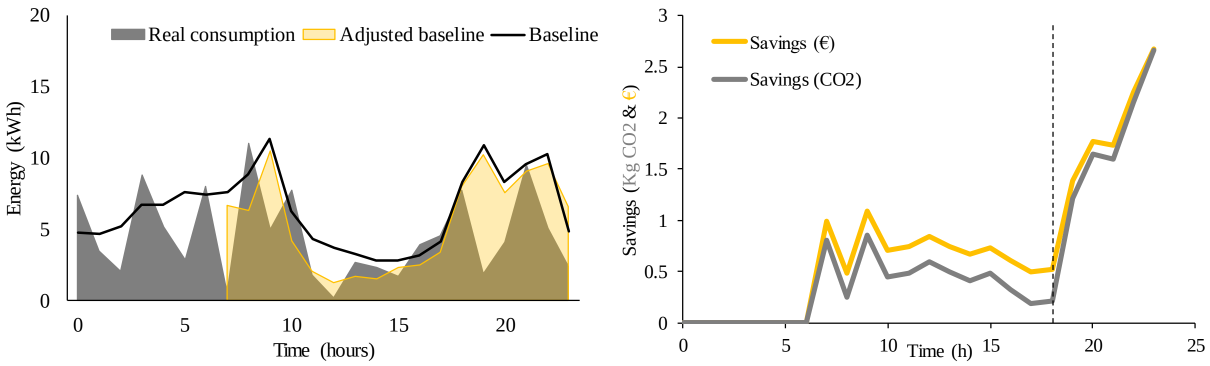

Figure 7: Results from SABINA. Left) Real versus baseline and adjusted baseline consumption. Right) Evolution of economic and environmental savings.

If compared to the baseline expected during the day ahead (black line in Figure 7) instead of that of the hour prior to the activation (yellow area), these results are even better, as the prediction was to consume more and savings result in 5.28 kg of CO_2 eq. emissions and 4.88€. Note that, in these cases, the weight of the balancing market payments is relatively low. Nonetheless, it was observed that the real consumption curve (grey area) after 19h was significantly lower than what was expected. This situation might be explained by the household occupancy, indicating how difficult is to predict the stochastic events of households. Therefore, if the calculations are done taking the hours from the activation until just before this unpredictable change in the building's consumption, results are less attractive, as savings until 19h are reduced to 0.21 kg of CO_2 equivalent emissions and 0.52 €, which represent a reduction at the end of the day of about 2% and 5% respectively. Nonetheless, in these cases, the payments from balancing markets gain relevance, weighting 68% of the total revenue. These results indicate that savings per kWh shifted are: 0.027 kg of CO_2 equivalent per kWh and 0.065€/kWh considering juts a 12h rebound effect curve.

Finally, similarly to what occurs to REFER's results, the additional incomes related to the carbon trade markets do effectively present a minor improvement of the economic results in SABINA. As mentioned in section 3, the introduction of this economic parameter had no impact on the optimization. Thus, considering that emissions savings correspond to 0.21kg of CO_2 eq., this makes 0.02€ to be added to the economic savings, which means an increase of 3.8% considering a CO_2 price of 95€/tCO_2 eq.

		SABINA	**REFER**
Total	CO_2 savings	0.21 kg (2%)	4.79 kg (20%)
	Economic savings	0.52 € (5%)	18 € (26%)
Per kWh shifted	CO_2 savings	0.027 kg	0.024 kg
	Economic savings	0.065 €	0.090 €

Table 3 Resume of CO2 and economical savings in the two projects considered

From Table 3 someone might retrieve that REFER's DA results, in relative terms of emissions savings, are incredibly better than those of SABINA (20% vs 2%). Note that this is not entirely true, as SABINA buildings do have an AEMS that already reduce the consumption of the building and, thus, the MIDA results refer only to the activation, having no capacity to effectively reduce the consumption of REFER's library, which has a non-optimized consumption strategy. In addition, the REFER DA has no limitations regarding the number of activations, while in the SABINA the DA can activate the flexibility just once per day. In fact, when looking to the savings per kWh shifted by the DA, the SABINA algorithm performs better in terms of CO_2 savings, while the REFER performs better when looking at the economical savings. This is due to the different objective of the DA.

5. CONCLUSIONS

This study presents two different centralized strategies for DA. The first one (REFER project) has higher computation efforts and complexity while the second one (SABINA) is easier to deploy but needs high performant and prepared AEMS in the buildings of its portfolio to work with. Additionally, REFER's approach shows faster reactivity, as the DA is the one receiving the requests, taking the decisions of what to activate and sending set-points to these elements that will immediately respond to that request. On the other side, following SABINA's configuration, the MIDA does not knows the real state of elements in the building, having to first ask for an update of the building's flexibility capacity to ensure that they will respond positively. Then the AEMS has to compute the request, send a response back to MIDA forcing it to re-compute the allocation of capacity through its portfolio. Then, MIDA asks for the final request of energy and the AEMS should re-compute the set-points of its elements to effectively deliver/consume that amount of energy. All this process takes several minutes, which difficult its entrance in fast-response markets. The response could certainly be faster by supressing some of the steps, but results could seriously deviate from what was expected.

To improve results, further development should be considered in forecasting the use of electricity in households, as the baseline versus the real consumption can notably differ from one day to another. However, tertiary buildings have a more trustable forecast, as the opening and closing hours are clear, special events are scheduled with enough time to inform (if necessary) and unexpected energy consumption changes out of opening hours rarely occurs.

Comparing both aggregators, it is visible how the driver has an impact on the results, since the ratio between the amount of economic savings versus kWh shifted is higher in the REFER, while the kg of CO_2 eq. emissions saved per kWh shifted is higher in SABINA, who's objective is to reduce emissions rather than incentivize economically the consumer. However, in both cases, DR activities reduce both the building CO_2 emissions and the electricity bill.

Seeing the results from both projects, if buildings are meant to participate offering ancillary services through their flexibility, it is of major importance to consider asymmetric bids. It is clear that, from a building perspective, they have higher capabilities to increase consumption, offering downwards capacity, while the availability of upwards capacity (decrease their consumption) is scarce or inexistent in many hours of the day.

The DA approach in REFER project is much more intrusive from a prosumer perspective, as it takes valuable information of the use and set-points of the devices in the building. This could carry out more intense cybersecurity and personal use of data protections. On the other side, the approach in SABINA uses only the information send by the AEMS, leaving personal use-of-energy information harder to reach by third parties.

Adapt the consumption to the production produces ever less emissions than to adapt the production to the consumption, since building emissions are reduced avoiding the activation of pollutant conventional power plants. In addition, DR can avoid the construction of new peak power plants and reduce investments in grid reinforcement, but these environmental benefits are difficult to count, as no methodology has been deployed yet.

Although results seem good enough, the margin obtained is yet not enough for massive deployment, as the costs of deployment were not included in the study. Neither the introduction of environmental incentives as the carbon trade show relevant improvements in the DA business model, which might be an indicator of how far this carbon trade price is still from something realistic to activate the needed environmental change. Further research should focus in finding new methods to account CO_2 savings from DR, since long term benefits are not kept into account in this study.

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